On-Pet Interaction

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Fig. 1. Interaction scenarios of on-pet interfaces. Left: A user shakes the dog's paw gently to open the light at the entrance (IoT Devices Control); Middle: A user performs stroking gestures on the pet to turn pages in a tablet reading app (System Control); Right: A user anchors a flashcard app on the pet in AR to recite Russian vocabularies while walking (Glanceable Display Anchors).

Disclaimer: This work DOES NOT intend to harm human-pet/animal relationships or use pets/animals as a "tool". As mentioned in our design considerations (C1 in Section 3.1), it is essential to satisfy both pets and users. We also acknowledge that "pets/animals cannot consent" at present, and there are many ethical considerations that need to be done before using on-pet interfaces. Nevertheless, this work looks at on-pet interaction from a naïve design perspective, hoping to expand the interaction horizons.

Abstract: This work investigates on-pet interaction, leveraging pet body as an input or output platform for computing purposes. We explore pets' unique features as a living interface. We further propose design considerations, a design space, and use cases, where we illustrate the example use of the interface for system controls and as information display anchors. We also develop a proof-of-concept prototype and conduct an initial evaluation. Our results demonstrate the feasibility of on-pet interaction.

1 INTRODUCTION

Human-computer interaction research has increasingly used objects and artifacts distributed at different time and space (e.g., human skins [8], walls [17], and tables [11]) as communication media with computing systems. Pets, as human companions, have not yet been proposed as an interaction medium, while they possess unique features for designs—they are alive creatures that own great autonomy comparing to non-living interfaces and also have an existing intimate relationship with their owners (users).

To fill this gap, this work explores on-pet interaction, leveraging pet body as an input or output platform for computing purposes. We consider a set of design considerations, including the satisfaction of both pets and users, the need for fast personalization and short-term usage of the interface, and the requirement of system robustness and reliability. We further introduce a three-dimensional design space considering the interfaces' input and output and the user and the pet's relative motion. After that, we provide two example application scenarios of on-pet interaction for system controls and as information display anchors, which can inspire future designs. Finally, we probe into one interaction scenario with a proof-of-concept prototype and conduct an initial evaluation. Our research demonstrates the potential usefulness and feasibility of on-pet interaction.

2 RELATED WORK

On-pet interaction lies under the broad concept of ubiquitous computing and ubiquitous interaction [11, 15]. Other than traditional mouse+keyboard and touchscreen input, existing research has explored various interaction paradigms such as in-air gestures [2] and input on human skin [8] and everyday objects [10, 11].

Comparing to static interfaces such as walls [17] and tables [11], more close to on-pet interaction are interfaces that own some dynamic features (e.g., robots [1, 13], self-actuate devices [12], or deformable objects [3]). For example, recent research appropriated quadcopters as interactive props to provide haptic feedback in virtual reality systems [1] and configured self-actuated shape displays to enable computing system manipulation [13]. As interfaces, pets can also move dynamically as quadcopters and change their postures (shapes) as shape displays. Unlike those existing interfaces, however, pets possess greater autonomy as living creatures, which reveals new design challenges and opportunities. Furthermore, pets may have formed a more intimate relationship with humans than non-living artifacts, and human-pet interaction (for computing purposes in our case) is suggested to have positive effects on users' mental and physiologic health status [6].

Another related idea is on-body (on-skin) interaction [7, 8], using human bodies (skins) as input surfaces and displays. As an emerging interface, the human body may afford similar interactions as the pet body, allowing gesture input like stroking, grabbing, and touching [14]. However, "borrowing" another person's body like on-pet interaction for computer input/output may pose social and acceptability concerns.

3 ON-PET INTERACTION

We define on-pet interaction as leveraging pet body as an input or output platform for computing purposes. Comparing to existing interfaces, on-pet interaction has the following unique properties:

- Pets are alive interfaces, which own great autonomy comparing to non-living interfaces.
- There are different types of pets, and even the same type of pets have various features and personalities.
- There are normally existing intimate relationship between users and their pets.

Those features unleash new design challenges and opportunities. Based on the unique properties of on-pet interaction, we proposed the following design considerations.

3.1 Design Considerations

Due to the unique features of on-pet interfaces, we made the following considerations when designing on-pet interaction.

C1. *On-pet interaction needs to satisfy both users and pets.* When interacting with computing devices through on-pet interfaces, users need to consider pets' needs and respect their dignity. For example, use gentle gestures on certain petted areas tailored for the pet (e.g., stroking on its back) to ensure pleasant and safe human-pet contact [5, 9]. Ideally, we should avoid instrumenting sensors on pets to capture the interaction gestures; a more acceptable approach may be placing sensors on the users' side (like using a smartwatch).

C2. *On-pet interaction demands fast personalization.* There are different types of pets, and the same types of pets can have different features (like body shapes) and personalities (e.g., preferred petting gestures and areas). Also, users may favor different ways of petting. Therefore, on-pet interfaces have to adapt to each person's and pet's needs quickly.

C3. *Preparing on-pet interaction for only short-term usage.* Since pets are living creatures and can leave the interaction context at any time, on-pet interfaces should only be prepared for short-term usage. They should be able to switch to other alternative interfaces once pets are no longer available for interaction.

C4. *On-pet interaction needs to be robust and reliable.* As a general requirement for developing user interfaces, the technologies need to ensure on-pet interaction is robust and reliable to guarantee its usability.

3.2 Design Space

We came up with the following design space based on the features and design considerations regarding on-pet interaction.

D1. *Input*: User input can be either *on-pet* or *off-pet*. On-pet input means that users need to touch directly on pets to enter information to computing systems (e.g., using on-pet gestures like stroking). In contrast, off-pet input implies that users interact with the on-pet interfaces remotely (e.g., through in-air gestures). Different input might require the use of different sensors and modalities.

D2. *Display*: Computer information can be displayed either *on-pet* or *on other devices*. For example, users might want to have information displayed close to and anchored on their pets (e.g., with AR glasses), or displayed across other devices [4] (e.g., on a tablet, a PC screen, or a smartphone).

D3. *Relative Motion*: The relative motion of a user and a pet can be *static*, *constrained*, or *free*. Pets can be relatively static (e.g., lying aside the user) if considering the user as a reference point. They may be constrained within a certain distance but still can be seen by the user (e.g., kept on a leash). In some cases, they move around the space freely and can be out of the user's sight (e.g., running freely on the grass and getting occluded by trees [16]).

3.3 Example Uses

We illustrate the example usage of on-pet interfaces through the following two interaction scenarios.

3.3.1 Scenario 1 (Figure 1 Left, Middle) – For Relative Static Motion. Alice comes back home after school, and her pet dog is welcoming her warmly at the door. She shakes the dog's paw gently, and the light opens at the entrance (*IoT Devices Control*). Alice then goes to sit on a soft to read her favorite book via a tablet and puts on her earphones to listen to music. Her pet dog is lying next to her, and her hand is placed on the back of the dog. She is somewhat lazy to put her hand back onto the touchscreen to turn pages, so she performs a stroking gesture on the back of the pet from head to tail to proceed to the next page of the book (*Reading Application Control*). She strokes on the back of the pet from tail to head to return to the previous page as she thinks she missed something there. She also notices the music from the earphones is too loud, so she strokes anti-clockwisely on the pet's back to turn down the volume (*Music Application Control*). After a while, she thinks she does not need the music anymore, so she double taps lightly on the pet's back to stop the music.

3.3.2 Scenario 2 (Figure 1 Right) – For Relative Constrained Motion. Alice is taking her dog for a walk, while she also wants to review some Russian vocabularies she learned yesterday in the class. So she grabs her AR glasses, anchors the flashcard app on the pet, and goes out for the walk. Along the way, she recites the vocabularies displayed on the pet and uses in-air gestures to flip to different flashcards. She also enjoys the road view without being distracted by always-on head-up displays in AR glasses (*Glanceable Content in AR Displays*) or hand-occupying devices like smartphones (*Hands-free Information Display Anchors*).

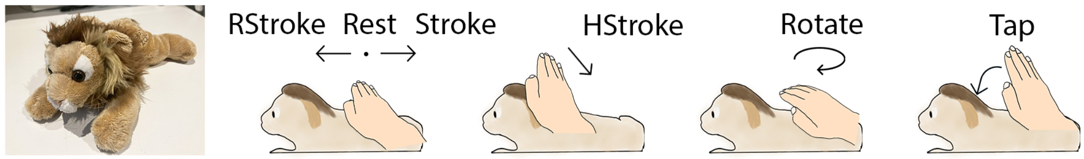

Fig. 2. Six on-pet gestures applied in our proof-of-concept demo.

4 IMPLEMENTATION AND EVALUATION

We probed into the interaction scenario when the relative motion of the user and the pet is static. We implemented a proof-of-concept demo that classifies on-pet gestures with a smartwatch. We further evaluated the prototype to test its ability of fast personalization and robustness.

4.1 Proof-of-Concept Demo

4.1.1 Device and Apparatus. We used an Apple Watch (Series 3) to capture on-pet gestures and a MacBook Pro with a Dual-Core i5 processor, 8 GB RAM, and an Iris Plus Graphics 640 graphical card to train the prediction model.

4.1.2 Model. We applied an activity classifier in Create ML, which is a shallow long short-term memory (LSTM) network, to predict targeted on-pet gestures. Processed device motion data, including the watch's orientation (3 axes) and user-generated acceleration vector (3 axes), were used as the input predictors. The training settings were as follows: maximum iterations = 20, batch size = 8, prediction window size = 10, and sample rate = 20.

4.2 Evaluation

4.2.1 Methodology. To provide training and testing data for the model under the current COVID-19 constraints, one researcher performed six on-body gestures on a toy pet (as shown in Figure 2). The six on-pet gestures were:

- *Stroke*: Stroking the back of the pet from head to tail.
- *RStroke*: Stroking the back of the pet from tail to head.
- *Rest*: Resting the hand on the pet.
- *HStroke*: Stroking the head of the pet.
- *Rotate*: Performing hand rotation on the back of the pet.
- *Tap*: Tapping the back of the pet lightly.

The researcher repeatedly performed each gesture 50 times in a 1 second time window with 10 frames per second logging rate. The smartwatch beeped every time to indicate the start of each trial. Among the 50 trials, 5 trials (10%) were used as training data, and the rest 45 trials (90%) were used as testing data. In all, we collected 30 trials of training data (6 on-pet gestures $\times$ 5 trials) and 270 trials of testing data (6 on-pet gestures $\times$ 45 trials).

4.2.2 Results and Discussion. After training the model, the training accuracy was 100%, and the overall testing accuracy was 93.7%. The confusion matrix was summarized in Table 1. The model accurately classified the *Stroke*, *RStroke*, *HStroke*, and *Rest* gestures, but occasionally miscategorized *Rotate* and *Tap* to other gestures. The overall testing accuracy was reasonable, given the small set of training data.

Table 1. Confusion matrix of the six on-pet gestures. The overall testing accuracy is 93.7% with 5 training samples (10%) and 45 testing samples (90%) for each gesture.

	Stroke	*RStroke*	*HStroke*	*Rest*	*Rotate*	*Tap*
Stroke	100%	0%	0%	0%	0%	7%
RStroke	0%	100%	0%	0%	2%	0%
HStroke	0%	0%	100%	0%	4%	16%
Rest	0%	0%	0%	100%	4%	2%
Rotate	0%	0%	0%	0%	87%	0%
Tap	0%	0%	0%	0%	2%	76%

Our evaluation, though preliminary, indicated that current technologies could support quick personalization with a small amount of training data (5 trials for each gesture in our case) and quite robust classification of on-pet gestures (with an testing accuracy of 93.7%), demonstrating the feasibility of our concept and designs.

5 CONCLUSION AND FUTURE WORK

In this research, we explored on-pet interaction, which leverages pet body as an input or output platform for computing purposes. We laid out design considerations, a design space, and two use case scenarios regarding on-pet interfaces. Further, we implemented a prototype probing into the condition when the user and the pet were relatively static and conducted an initial evaluation. Our research showed the potential usefulness and concept feasibility of on-pet interaction. Future work can investigate deeper from both the technology side and the users' side. For example, we can explore different sensing modalities and intention prediction models to allow quick on-device learning of a large set of input gestures. Moreover, we can conduct more extensive user studies with real pets to gather users' feedback regarding on-pet interfaces and their potential effect on users' emotional states.

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